URBAN MOBILITY & EQUITY CENTER

Final Report

Analysis of Interrelated Network Improvement Alternatives

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16. Abstract This project developed methods for optimizing the long-term development of road networks by developing algorithms for selecting, sequencing and scheduling interrelated improvements, which change flows through the networks. It also compared how network performance can be evaluated as a network's configuration evolves, using either a fast traffic assignment algorithm or the slower but more realistically precise microscopic simulation model INTEGRATION. The results indicate when and to what extent the traffic assignment algorithm can approximate the simulation results. They demonstrate the potential value of hybrid methods in combining initial search with traffic assignment and refined search with microscopic simulation.		
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Executive Summary

The development of transportation networks that can satisfy evolving travel demand characteristics within specified resource constraints requires decisions about interrelated projects. These projects must be identified, specified, evaluated, prioritized, and scheduled, subject to various constraints regarding financing, construction times and resources, accessibility, and equity. Commonly used evaluation practices are inadequate for projects in transportation networks, since they mostly neglect possible interrelations among projects due to non-linearly additive benefits, costs, budget constraints, and other factors. The benefits of link additions or improvements are especially interrelated since they affect the flows and benefits of other links. For example, if the capacity increases in one link of a network, congestion and average travel times tend to increase in other links that are "in series" with it and decrease in its "parallel" links.

This project develops methods for optimizing the long-term evolution of transportation systems by improving previously developed methods for evaluating, selecting, sequencing, and scheduling interrelated alternatives in road networks. It demonstrates how complete schedules of network improvements can be evaluated with either a very fast traffic assignment algorithm or with a slower microscopic simulation model that is better at capturing the complexities of traffic flows in congested networks. The obtained results indicate to what extent and in what situations the faster algorithm can approximate the more reliable evaluation results obtained through the microsimulation when selecting and scheduling interrelated improvements in road networks. Such results also indicate the potential value of hybrid methods for solving network development problems by combining a rough initial search with approximation methods with a refined search through microscopic simulation.

Through this project, several methods have also been developed for optimizing network development schedules based on various objectives and constraints while considering uncertainties regarding future demand, budgets, costs and construction times. Although this project has supported part of the work in one Ph.D. dissertation and will very likely yield future journal publications, the remainder of this report includes only one paper that has been submitted to date and is currently under review for presentation at the 2024 Annual Meeting of the Transportation Research Board and for publication in the Transportation Research Record.

The methods developed in this project can improve the ability of various transportation agencies to efficiently allocate their limited resources, coordinate their development plans, deal with disruptions, and generally improve the capacity, service quality and overall performance of transportation systems.

Optimized Road Network Development with Comparison of Microsimulation and Traffic Assignment

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ABSTRACT

A bi-level model was formulated to optimize the selection and schedule of interrelated improvement projects in road networks. The lower level performs user-equilibrium (UE) traffic assignment and computes hourly total travel time cost. The upper-level model seeks the network improvement plan that minimizes the present value of costs (PVC). Any sequence of improvement projects is mapped to a unique schedule based on binding budget and work time constraints. Approximation methods are then applied to estimate the effects of demand growth and cost discounting in the planning horizon and determine budget-ready times of projects with internal budget supply. The model is demonstrated in a numerical case, where the improvement plan is optimized by a genetic algorithm (GA), and two methods for the lower-level computation–Frank-Wolfe traffic assignment and microscopic simulation–are compared in evaluating travel time cost. As the demand and congestion level increases, the absolute and relative values of discounted travel time cost evaluated by the F-W algorithm diverge further from those evaluated by microscopic simulation, which is treated as a superior method to F-W for capturing dynamics of individual vehicles.

Keywords: Interrelated Projects, Road Network, Network Development Optimization, Microscopic Simulation

INTRODUCTION

In a road network, vehicles move through links and nodes under various constraints to satisfy demands from users in the network. When deciding on a long-term network improvement plan over a planning horizon, multiple projects are possible, each having its own requirements for labor, equipment, materials, budgets, and construction durations. Implementation and completion of an improvement project reduces the systemwide travel time by increasing capacities of network components or adding new links into the network. One problem for road network managers is to select, sequence, and schedule these projects to minimize project costs and cumulative travel time over the planning horizon.

The candidate projects can be regarded as “interrelated” if the effects of individually completing these projects on network performance cannot be simply aggregated for evaluating their combined effect. To capture this interrelation, measures of network performance (e.g., total travel time or cost) must be evaluated for each network configuration upon completing specific projects. In road networks, such evaluations are commonly conducted by computing the total travel time under some type of traffic flow pattern (e.g., user equilibrium). Various methods exist for travel time computation. Some methods take advantage of link congestion functions and perform iterative traffic flow assignments based on shortest paths, while others perform traffic simulations that incorporate more real-world factors such as car-following behavior and delays at intersections. While the former methods are much more computationally effective than the latter, they sacrifice most of the detailed mechanics of road traffic and may show inaccuracies in estimating traffic measurements for practical decisions. It is desirable to make comparisons between these methods to examine the conditions under which each type of method can provide satisfactory results with acceptable computation costs.

The following sections review some relevant studies; formulate the bi-level optimization model for selection, sequencing, and scheduling of road improvement projects; present methods for solving the problem; and discuss some numerical results which demonstrate and compare the methods.

LITERATURE REVIEW

In various transportation networks, optimizing the selection and scheduling of interrelated projects is necessary for maximizing total benefit or minimizing total cost over a specified planning horizon. Earlier applications of this problem in transportation include studies for inland waterways [1-2] and road networks [3-5]. In recent years such studies have appeared for road networks [6-13] as well as for rail and rail transit networks [14-16].

The relevant studies on this problem are listed in Table 1, which classifies some characteristics of previous studies in this field. First, various methods for solving such problems have been developed for several kinds of transportation networks, mostly using heuristic methods such as variations of genetic algorithms. Second, in more recent studies the problem formulation was usually bi-level, where flows in the network were assigned at the lower level and the selection and scheduling of projects was optimized at the upper level for a specific objective function (OF) computed over the planning horizon. In these bi-level models, the OFs were associated with costs, benefits, or travel time, and the project interrelation was captured by the projects' resulting changes in the flow-related network performances. In other words, the project interrelation could not be explicitly expressed in OFs or constraints. Third, the implementation of projects was most commonly subject to budget constraints and was also affected by resource and precedence limitations. In most studies, however, the budget supply was limited to external sources. In many actual cases, revenues (e.g., tolls) can be collected from the network flows as an "internal" budget supply for project implementation. Fourth, the problem formulation mostly allowed budget and demand levels to be time-varying over the planning horizon, which was more commonly discrete than continuous. A discrete-time planning horizon facilitates computation of OFs, but limits the flexibility of determining project implementation times.

Microscopic simulation plays a crucial role in assessing the impact of improvement projects on road networks. It offers a detailed perspective on the interactions between individual vehicles and traffic control devices, such as traffic lights, stop signs, and yield signs. These interactions not only slow down traffic and cause local delays but also generate shockwaves that affect downstream traffic at a broader level. When capturing the intricacies of individual vehicle maneuvers within the network and their aggregated effects on traffic flow, microscopic traffic simulation becomes essential. Over the past 70 years, microscopic traffic simulation has proven to be a valuable and cost-effective tool in various traffic studies for research and practical purposes. Its applications include feasibility studies, sensitivity analyses, and virtual demonstrations of different traffic scenarios. The Federal Highway Administration (FHWA) has compiled a list featuring over 30 well-known microscopic simulation tools [17]. Alongside the one used in this paper, INTEGRATION, other prominent tools include VISSIM, AIMSUN2, CORSIM, and MicroSim, among others.

This paper contributes to the optimization of selection and scheduling of interrelated projects in road networks in the following aspects:

1) The following features are combined. Internal as well as external budget sources and a continuous planning horizon are considered jointly, allowing more flexibility in deciding

when to start and complete projects. Effects of demand growth over the planning horizon are evaluated with an approximation method.

2) Overlapping of project implementation periods is allowed. Since traffic links have reduced capacities during construction, overlapping project implementations result in more potential network configuration states.
3) This paper presents a comparative analysis of two methods for evaluating network performance: traffic assignment and microscopic traffic simulation. The study delves into the discrepancies observed between these methods across different levels of travel demand. The insights drawn from the conclusions of this paper facilitate a deeper understanding of the appropriate applications of each method, thereby enhancing the interpretation of the modeling results.

Table 1 Relevant studies on selection, sequencing and scheduling interrelated projects

Authors and date	Objective functions	Continuous planning horizon?	Optimizing selection & schedule?	Solution methods	Applications	Constraints	Time varying?
Hu & Schonfeld (1984) [3]	Improve level of service (traffic flow) by max. annual net benefit	No	No (sel. only)	IMSL routine ZXMIN	Various road projects & their combinations	None	Demand
Wei & Schonfeld (1994) [4]	Min. PV of total user travel time costs plus project costs	No	Yes	Branch and bound, with artificial neural network for UE	Link capacity expansion (road)	Budget, project continuity	Demand
Jong & Schonfeld (2001) [1]	Min. PV of total waiting time cost	Yes	Yes	GA	Lock improvement (waterway)	Budget	Budget, demand
Wang & Schonfeld (2005) [2]	Max. PV of total user benefits	Yes	Yes	GA with a waterway simulation	Lock improvement (waterway)	Budget	Budget, demand
Tao & Schonfeld (2007) [5]	Min. total user travel time (with a random term), based on UE traffic	No	Yes	Island model (GA extension)	Link improvement (road)	Budget	Budget, demand
Li et al. (2013) [6]	Max. total benefit measured by net reductions of agency and user costs, based on traffic assigned by MMCN	No	No (sel. only)	Multi-commodity min. cost network, life-cycle cost analysis, hypergraph Knapsack	Various road projects (widen-ing, new link, interchange…)	Budget	Budget, project cost, demand
Bagloee & Asadi (2015) [7]	Max. total benefit measured by total travel time reduced based on static traffic assignment	Yes	No (sched. only, se-quencing)	Gradient-based hybrid GA and ant colony on NN	Road addition	None	Demand
Miandoabchi et al. (2015) [8]	Min. total travel time and CO emission (bi-objective), based on UE traffic	No	Yes	NSGA-II (a GA variant) and B-cell algorithm	Lane and road addition, lane allocation and alteration	Budget	Demand
Gong & Fan (2016) [9]	Min. excessive cost, based on UE traffic	No	No (sched. only)	GA, with F-W for UE	Mtn. (road)	A set of required projects	None

Hosseininasab et al. (2018) [10]	Multi-objective: min. total travel time, max. user satisfaction over time, and max. spatial equity, based on UE traffic	No	Yes	2 approaches combining FW, GA, simplex phase I, & knees identification	Link addition (road)	Budget, technical limitation	Budget, demand
Dao et al. (2019) [14]	Min. total renewal and unavailability costs, with economy of scale	No	Yes (recurrent)	Triple-prioritization rule	Infrastructure renewal in rail network	Possession time, network constraints, due-date	Maximum number of possession at location
Peng et al. (2019) [15]	Min. PV of user cost plus supplier cost	Yes	Yes	Customized GA	Investments in rail transit network	Budget (with internal supply)	Demand
Shayanfar & Schonfeld (2019) [11]	Min. PV of total system cost (including vehicle operation & safety)	Yes	Yes	GA, with F-W for assessment	Lane addition & widening (road)	Budget with fuel tax supply	Budget, demand
Miralinaghi et al. (2020a) [12]	Min. total travel delay, based on UE traffic	No	Yes	“Active-set” algorithm	Road capacity improvement, link addition, mtn.	Budget	Budget, demand
Miralinaghi et al. (2020b) [13]	Min. weighted total travel cost minus total business revenue, based on UE traffic	No	No (sched. only)	“Active-set” algorithm	Road capacity improvement, mtn.	Budget, required set of projects	Budget, demand
Mohammadi et al. (2020) [16]	Max. weighted total quality of the network based on Track Quality Index	No	Yes (recurrent)	Greedy heuristic for an initial solu-tion to MILP and its robust version	Various rail freight network mtn.	Budget, mtn. thresholds, time allowed, resources	Constraint parameters, effects, and costs of mtn.

mtn. = maintenance; max. = maximize; min. = minimize; sel. = selection; sched. = scheduling

PROBLEM FORMULATION

Lower-level traffic assignment model

In a road network, there are nodes $n \in N$ and links $a \in A$. Each link has its length d_a in miles. For each OD pair $w \in W$ in this network, q_w vehicles/hour travel through multiple connecting paths $p \in P_w$.

Each link has its actual capacity k_a in vehicles/hour. Travel time through each link in hours, denoted as t_a, equals t_a^0 when there are no vehicles on the link. With a traffic flow of x_a in vehicles/hour, the travel time t_a is given by the following congestion function proposed by the Bureau of Public Roads (BPR) [18]:

$$t_a(x_a) = t_a^0[1 + 0.15\frac{x_a}{k_a}]^4 \tag{1}$$

For each OD pair w, the set of all possible simple paths in the network is denoted as P_w, and the number of vehicles in an hour using path $p \in P_w$ is denoted as f_p^w. According to the user equilibrium (UE) conditions proposed by Wardrop [19], the following nonlinear programming problem is formulated for the road traffic:

$$Min \sum_{a \in A} \int_0^{x_a} t_a(x)dx \tag{2}$$

subject to:

$$\sum_{p \in P_w} f_p^w = q_w, \forall w \in W \tag{3}$$

$$f_p^w \geq 0, \forall p \in P_w, w \in W \tag{4}$$

$$x_a = \sum_{w \in W} \sum_{p \in P_w} f_p^w \gamma_{a,p}^w, \forall a \in A \tag{5}$$

The objective function to be minimized in (2) is the sum of integrals of the link congestion functions with respect to traffic flows. Constraints (3) and (4) ensure that for each OD pair, the sum of all non-negative traffic flows on different paths equals the OD pair's total traffic demand. The traffic flow through each link is given by constraint (5), where $\gamma_{a,p}^w$ is a binary indicator that equals 1 only if link a is used by path $p \in P_w$ of OD pair w. When the optimized UE assignment is reached, no vehicle can reduce its travel time by shifting its route. The UE traffic flow on link a per hour is denoted by x_a^{UE}. The hourly total travel time cost in the network is:

$$Z_{UE} = v \sum_{a \in A} x_a^{UE} t_a(x_a^{UE}) \tag{6}$$

where v is the value of time in \$/vehicle/hour.

Upper-level model for optimizing selection and scheduling of improvement projects

In a planning horizon of T years, there are $|\Lambda|$ available projects for improving the road network. The number of projects $L(=|\sigma_{imp}|)$ to be implemented in an improvement sequence $\sigma_{imp} \in \Sigma_{imp}$ satisfies $0 \leq L \leq |\Lambda|$. Then, there are $|\Lambda|!/(|\Lambda| - L)!$ possible sequences with L improvements. The i^{th} improvement in the sequence σ_{imp} is denoted as σ_{imp}^{i}, if $|\sigma_{imp}| \neq 0$. Considering that capacities of some links are reduced during construction of a project, both the start and the completion of each project lead to changes in network configuration (including availability of nodes and links as well as link capacities). The original network configuration is denoted as κ_0, and the updated configurations following the first, second, and later starts/completions of improvements are denoted as $\kappa_1, \kappa_2, \ldots, \kappa_{2|\sigma_{imp}|}$. These configurations start at $\tau_0, \tau_1, \tau_2, \ldots, \tau_{2|\sigma_{imp}|}$ years into the planning horizon, and they last for $\varphi_0, \varphi_1, \varphi_2, \ldots, \varphi_{2|\sigma_{imp}|}$ years, respectively.

With an annual growth rate of demand g, the hourly demands of all OD pairs increase at a constant annual rate:

$$q_w(\tau) = (1 + g)^{\tau} q_w(0) \tag{7}$$

where τ is the number of years elapsed in the planning horizon. $q_w(0)$ denotes the hourly demand of OD pair w at the year zero, and this is a fixed parameter.

With a time-varying demand level, the average hourly total cost of travel time under user equilibrium (Z_{UE}) as obtained at the lower-level model can be treated as a function of τ. When evaluating the value of $Z_{UE}(\tau)$, different improvement sequences σ_{imp} lead to different time spans of network configuration κ_i $(0 \leq i \leq 2|\sigma_{imp}|)$. Let $Z_{UE}^{\kappa_i,\sigma_{imp}}(\tau)$ be a continuous function that is integrable in the time interval where the network is in phase i with configuration κ_i given the improvement sequence σ_{imp}. The present value (PV) of cumulative total cost of travel time over the planning horizon with the sequence σ_{imp} is:

$$Y_{\sigma_{imp}} = H \sum_{i=1}^{2|\sigma_{imp}|} \int_{\tau_{i-1}}^{\tau_i} \frac{Z_{UE}^{\kappa_i,\sigma_{imp}}(\tau)}{(1 + r)^{\tau}} d\tau \tag{8}$$

where H is the number of effective hours in a year, and r is the annual interest rate. This equation serves as a general formulation, while the actual computation of $Y_{\sigma_{imp}}$ uses the approximation provided in the "Methods" section.

Given the evaluated improvement sequence σ_{imp}, the total construction (implementation) cost of the i^{th} project in the sequence (σ_{imp}^{i}) is $C_{\sigma_{imp}^{i}}$. Let $\beta_{\sigma_{imp}^{i}}$ be a binary indicator that equals 1 if σ_{imp}^{i} can be completed within the planning horizon. The detailed rules for determining $\beta_{\sigma_{imp}^{i}}$ are explained in the following section.

In the upper-level model, to optimize the selection and schedule of improvements, the objective is to find the sequence σ_{imp} that minimizes the present value of costs (i.e., PVC), which is the sum of cumulative travel time cost plus total project construction cost during the planning horizon:

$$Min\ PVC(\sigma_{imp} \in \Sigma_{imp}) = Y_{\sigma_{imp}} + \sum_{i=1}^{|\sigma_{imp}|} \beta_{\sigma_{imp}^i} \frac{C_{\sigma_{imp}^i}}{(1+r)^{\tau_{\sigma_{imp}^i}}} \tag{9}$$

where $\tau_{\sigma_{imp}^i}$ denotes the time when the cumulative available budget becomes sufficient to pay for project σ_{imp}^i. It is assumed that the payment from the available budget for project σ_{imp}^i occurs only at the time $\tau_{\sigma_{imp}^i}$. Rules for determining $\tau_{\sigma_{imp}^i}$ are explained in the next section. It should be noted that, for a given sequence σ_{imp}, its i^{th} project σ_{imp}^i is also the i^{th} project to start in the planning horizon, but not necessarily the i^{th} project to be completed.

Constraints and rules for scheduling project implementation

In this section, constraints and rules for uniquely determining start and completion times of projects under a given improvement sequence σ_{imp} are presented. According to these rules, each project that reduces the hourly travel time cost is initiated and completed as soon as its benefits justify its cost, considering the current demand level and any binding constraints. This approach aims to maximize the cumulative savings in travel time cost over the planning horizon. The following assumptions are applied:

1) The initial available budget is zero. During the planning horizon, there is a constant monthly external supply of budget F, and available budget cannot be negative at any time.
2) A project cannot be completed until its funding is fully ready.
3) A constant small fraction μ of total travel time cost is treated as a toll usable as an internal source of budget.

Concurrent work on multiple projects is allowed. Given the sequence σ_{imp}, project σ_{imp}^i has its construction cost $C_{\sigma_{imp}^i}$ and its required work duration $\phi_{\sigma_{imp}^i}$. If there is only external budget supply, then $\max\{C_{\sigma_{imp}^i}/F, \phi_{\sigma_{imp}^i}\}$ years are needed to complete its construction. The times when the available budget reaches sufficiency for project σ_{imp}^i are given by

$$\tau_{\sigma_{imp}^i} = C_{\sigma_{imp}^i}/F + \tau_{\sigma_{imp}^{i-1}}, \qquad 1 \le i \le |\sigma_{imp}| \tag{10a}$$

If internal budget supply is available, however, $\tau_{\sigma_{imp}^i}$ is given by

$$C_{\sigma_{imp}^i} = \sum_{j=j_1}^{j_2} \int_{\tau_j}^{\tau_{j+1}} [F + \mu HZ_{UE}^{\kappa_j,\sigma_{imp}}(\tau)] d\tau, \qquad 1 \le j \le 2|\sigma_{imp}| \tag{10b}$$

subject to:

$$\tau_{j_1-1} < \tau_{\sigma_{imp}^{i-1}} = \tau_{j_1}, \qquad 2 \le i \le |\sigma_{imp}| \tag{11a}$$

$$\tau_{j_2} < \tau_{\sigma_{imp}^i} = \tau_{j_2+1}, \qquad 1 \le i \le |\sigma_{imp}| \tag{11b}$$

$$\tau_{\sigma_{imp}^0} = 0 \tag{11c}$$

where $\tau_{\sigma_{imp}^i}$ needs to be numerically determined using the methods provided in the "Methods" section. With internal and external budget supply, $\max\{\tau_{\sigma_{imp}^i} - \tau_{\sigma_{imp}^{i-1}}, \phi_{\sigma_{imp}^i}\}$ years are needed to complete the construction of σ_{imp}^i.

Whenever funding is completed for project σ_{imp}^i, the next project σ_{imp}^{i+1} in the sequence (if it exists) starts. If work duration is not yet reached for σ_{imp}^i, concurrent construction of σ_{imp}^i and σ_{imp}^{i+1} occurs. The durations of phases (φ_i) and their corresponding network configurations (κ_i) depend on starting and completion times of improvement projects. It is defined that Phase i starts from the i^{th} starting/completion time (τ_i) of all projects in the sequence σ_{imp} and ends at the $(i+1)^{\text{th}}$ starting/completion time (τ_{i+1}). If the starting/completion time of one project overlaps with that of another project (that is, $\tau_{i_1} = \tau_{i_2}, i_1 < i_2$), then there is a corresponding phase with zero duration ($\varphi_{i_1} = 0$). If the improvement sequence is not empty (i.e., $|\sigma_{imp}| \neq 0$), then Phase 0 has a duration of zero at the start of the planning horizon ($\tau_0 = \tau_1 = \varphi_0 = 0$). An example of determining the schedule for a sequence with 5 selected projects is shown in Figure 1, with given input parameters $C_{\sigma_{imp}^i}$, F, μ, and $\phi_{\sigma_{imp}^i}$. For the second and fourth project in the sequence, $\tau_{\sigma_{imp}^i} - \tau_{\sigma_{imp}^{i-1}} \geq \phi_{\sigma_{imp}^i}$, while for other projects $\tau_{\sigma_{imp}^i} - \tau_{\sigma_{imp}^{i-1}} < \phi_{\sigma_{imp}^i}$.

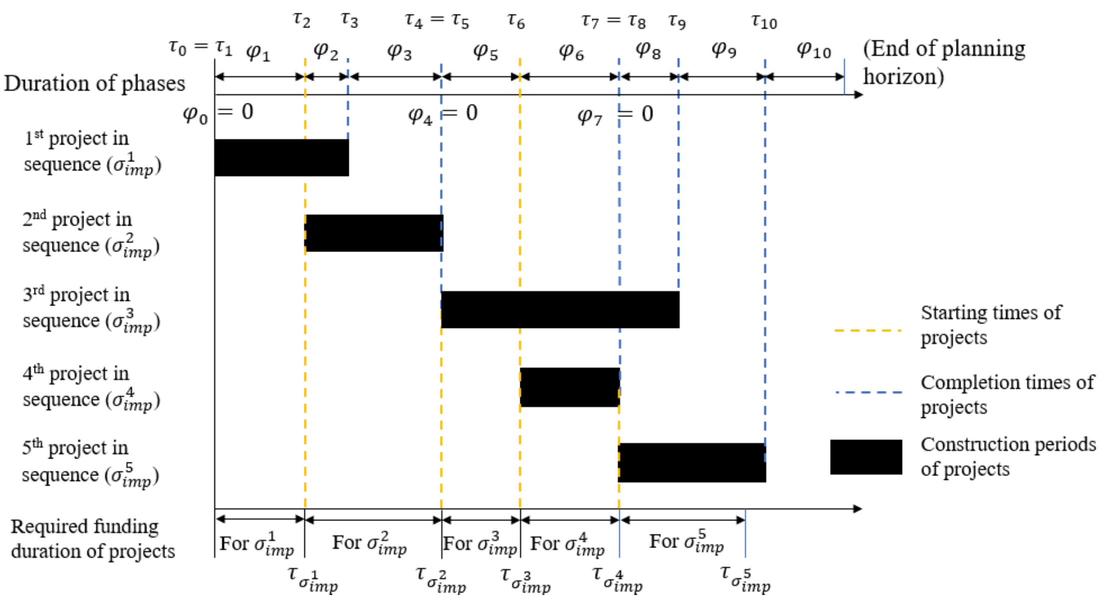


Figure 1 Determining the schedule for a sequence with 5 projects

In the example above, all projects in the sequence σ_{imp} are completed within the planning horizon. A rule is set for truncating project starting/completion times (τ_i) beyond the planning horizon. After determining raw values of $\tau_1, \tau_2, \ldots, \tau_{2|\sigma_{imp}|}$, if a specific time value τ_j satisfies $\tau_{j-1} < T \leq \tau_j$, then values of τ_i with $i \geq j$ are truncated to T. This means that phase $(j-1)$ must be terminated at the end of the planning horizon, and that all phases after phase $(j-1)$ have zero durations. Meanwhile, values of binary indicators $\beta_{\sigma_{imp}^i}$ in equation (9) equal to 1 by default. If a $\tau_{\sigma_{imp}^j}$ (budget-ready time for project σ_{imp}^j) satisfies $\tau_{\sigma_{imp}^{j-1}} < T \leq \tau_{\sigma_{imp}^j}$, then $\tau_{\sigma_{imp}^i}$ with $i \geq j$ are set to T, and binary indicators $\beta_{\sigma^i_{imp}}$ with $i \geq j$ equal to 0, which means that the j^{th} and later projects in the sequence cannot be funded within the planning horizon.

METHODS

Frank-Wolfe traffic assignment at the lower level

At the lower-level model, the Frank-Wolfe (F-W) algorithm [20] computes hourly total travel time cost in the road network at user equilibrium (Z_{UE}). The steps of this algorithm are shown below.

0) Initialization. Let flows on all links be zero and do all-or-nothing traffic assignment based on the free-flow travel times of links (that is, for each OD pair w, find out the path p with the shortest travel time, and let $f_p^w = q_w$ for this path). Compute the traffic flow vector $\{x_a^1\}$, and start iteration i=1.

1) At the start of iteration i, compute the travel time vector $\{t_a^i\}$ where $t_a^i = t_a(x_a^i)$ for each link. Then do all-or-nothing assignment based on $\{t_a^i\}$, and compute the resulting traffic flow to obtain the auxiliary flow vector $\{u_a^i\}$, which serves as an updated searching direction of traffic flows.

2) Find the optimal step length $\lambda_i \in [0,1]$ that moves the flow vector from $\{x_a^i\}$ to $\{x_a^{i+1}\}$. A bisection method is used to search for λ_i that satisfies the following equation:

$$\sum_{a \in A} (u_a^i - x_a^i) \cdot t_a[x_a^i + \lambda_i(u_a^i - x_a^i)] = 0 \tag{12}$$

3) Obtain the succeeding flow vector $\{x_a^{i+1}\}$ where $x_a^{i+1} = x_a^i + \lambda_i(u_a^i - x_a^i)$. Compute the relative gap between flow vectors $\{x_a^i\}$ and $\{x_a^{i+1}\}$ given by:

$$\Delta_x = \sqrt{\sum_{a \in A} (x_a^{i+1} - x_a^i)^2} \Bigg/ \sum_{a \in A} x_a^i \tag{13}$$

4) If the relative gap is below a pre-specified threshold, stop the iterative search and use $\{x_a^{i+1}\}$ as the final vector of UE traffic flow. Otherwise, loop back to step 1) and perform the next iteration.

Applying microscopic simulation at the lower level

An alternative lower-level method to compute Z_{UE} in the road network is aided by a microscopic simulation model. To conduct a thorough examination of vehicle operations within the network at a microscopic level, an agent-based traffic simulation model is essential. This model must accurately capture the dynamic maneuvers of vehicles in real-world scenarios, including interactions between vehicles, car-following behavior, gap acceptance for turns, weaving, lane changing, and more. For this purpose, the INTEGRATION trip-based microscopic traffic simulation model is adopted [21, 22]. It tracks individual vehicle movements from their origins to their destinations, providing a detailed resolution of one status update every 1/10 of a second. This level of granularity allows the representation of spatial variations in traffic conditions with considerable flexibility. Unlike traditional models that assume uniform traffic conditions along a link, INTEGRATION allows for continuous density variations along the link. This dynamic density variation is particularly useful in representing scenarios such as platoons departing from traffic signals and the propagation of shock waves both upstream and downstream along an arterial link. Over the last two decades, INTEGRATION has not only been validated against standard traffic flow theory [23-25], but has also been utilized for multiple studies where both a microscopic level of detail and a macro-level understanding of the impact on the traffic system are needed [26-28].

The INTEGRATION model computes delays by estimating the difference in travel time between the vehicle's instantaneous speed and free-speed every 1/10 of a second. Regarding the routing method and determination of the next downstream link, the INTEGRATION model offers multiple techniques, some of which are deterministic and static, while others are stochastic and dynamic. Among these techniques, this study employs the Frank-Wolfe routing algorithm, where link travel times are computed using a weighted average of multiple trees. This approach ensures a comprehensive analysis of vehicle movements while incorporating delays caused by traffic controls and congestion.

Upon completing the simulation with dynamic traffic assignment, the INTEGRATION model generates summarized statistics, which can be computed either by link, by vehicle, or for the entire network. In the summary output file for the network, the vehicle trips are counted as the total number of vehicles that complete their trips within the simulation period. To compute the hourly total travel time cost in the network (Z_{UE}) without directly using equations (1) to (5), the model sums up the trip times across all vehicle trips completed within the simulation period. This comprehensive approach allows for a detailed analysis of the traffic behavior within the network and will allow the comparison of the two modeling methods in later sections.

Approximating effects of demand growth and discount rate

When computing the present value (PV) of total travel time cost accumulated over the planning horizon with the improvement sequence σ_{imp}, as given by $Y_{\sigma_{imp}}$ in equation (8), the following approximation method is applied. The planning horizon is first divided into multiple equal-length sub-periods. Next, the starting and completion times of projects (τ_i) further divide existing sub-periods into shorter ones. From the earliest to the latest, these sub-periods are denoted by ε_1, ε_2, and so forth, and their corresponding midpoint times are denoted by τ_{ε_1}, τ_{ε_2}, and so forth. With the demand growth rate g, hourly demands (q_w) of all OD pairs at each midpoint time are obtained using equation (7). For each sub-period ε_i, using the midpoint demands and the corresponding network configuration κ_{ε_i}, the approximated hourly travel time cost is computed with the lower-level model:

$$\bar{Z}_{UE}^{\kappa_{\varepsilon_i},\sigma_{imp}} = Z_{UE}^{\kappa_{\varepsilon_i},\sigma_{imp}}(\tau_{\varepsilon_i}) \tag{14}$$

With the duration of this sub-period (φ_{ε_i}, in years), the hours in a year (H), and the discounting factor $(1+r)^{\tau_{\varepsilon_i}}$, the approximated PV of cumulative travel time cost over sub-period ε_i can be obtained. Finally, $Y_{\sigma_{imp}}$ is computed by summing up these PVs over all $|\varepsilon|$ sub-periods:

$$Y_{\sigma_{imp}} = H \sum_{i=1}^{|\varepsilon|} \frac{\varphi_{\varepsilon_i} \bar{Z}_{UE}^{\kappa_{\varepsilon_i},\sigma_{imp}}}{(1+r)^{\tau_{\varepsilon_i}}} \tag{15}$$

The iteration method for numerically finding the approximated time $\tau_{\sigma_{imp}^{i}}$ (the budget-ready time for the i^{th} project in sequence σ_{imp}) is illustrated in the flowchart in Figure 2 and in the changes on time axes in Figure 3.

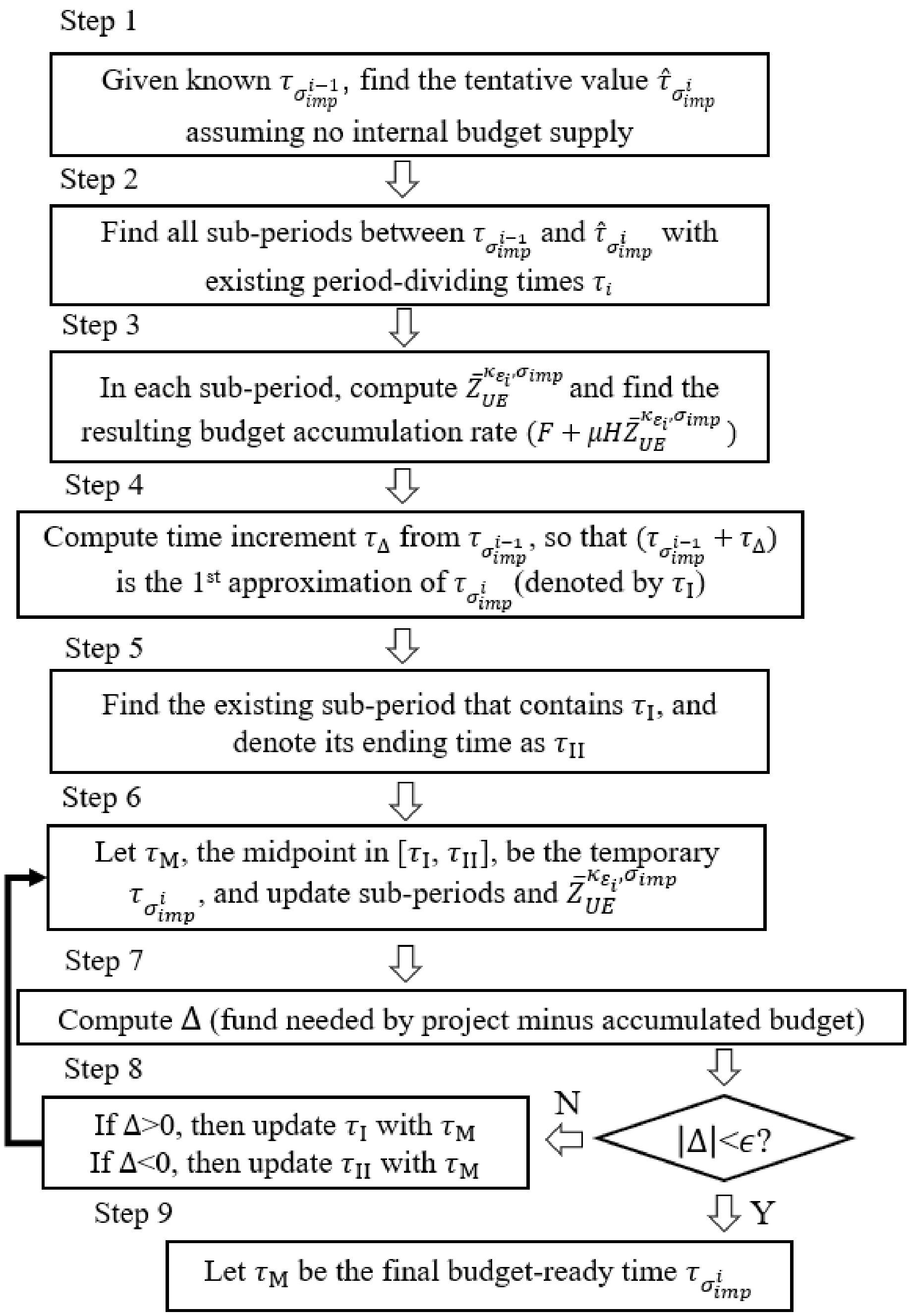


Figure 2 Steps for numerically determining the approximated budget-ready time

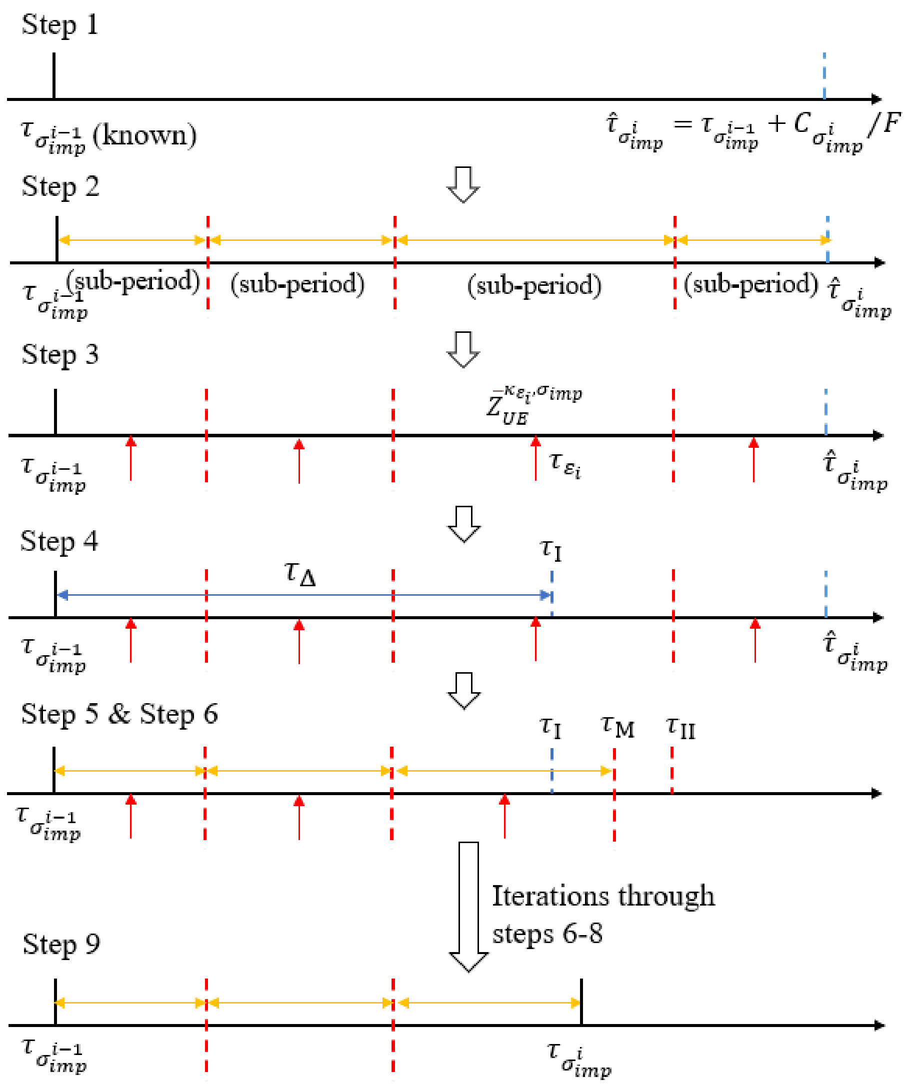


Figure 3 Changes on time axes while finding the budget-ready time

In Step 4, the time increment τ_{Δ} is determined with the following equations:

$$C_{\sigma^{i}_{imp}} = \sum_{j=j_1}^{j_2} \left(F + \mu H \bar{Z}_{UE}^{\kappa_{\varepsilon_j},\sigma_{imp}}\right) \cdot \min\left\{\varphi_{\varepsilon_j}, \max\left\{\tau_{\sigma^{i-1}_{imp}} + \tau_{\Delta} - \tau_{\varepsilon_j} + \varphi_{\varepsilon_j}/2, 0\right\}\right\}, j \geq 1 \qquad (16)$$

subject to:

$$\tau_{\varepsilon_{j_1-1}} < \tau_{\sigma^{i-1}_{imp}} < \tau_{\varepsilon_{j_1}}, \qquad 2 \leq i \leq \left|\sigma_{imp}\right| \qquad (17a)$$

$$\tau_{\varepsilon_{j_2}} + \varphi_{\varepsilon_{j_2}}/2 = \hat{\tau}_{\sigma^{i}_{imp}}, \qquad 1 \leq i \leq \left|\sigma_{imp}\right| \qquad (17b)$$

$$0 < \tau_{\Delta} < \hat{\tau}_{\sigma^{i}_{imp}} - \tau_{\sigma^{i-1}_{imp}}, \qquad 1 \leq i \leq \left|\sigma_{imp}\right| \qquad (17c)$$

$$\tau_{\sigma^{0}_{imp}} = 0 \qquad (17d)$$

In Step 7, the difference Δ is given by:

$$\Delta = C_{\sigma_{imp}^{i}} - \sum_{j=j_1}^{j_2} (F + \mu H \bar{Z}_{UE}^{\kappa_{\varepsilon_j},\sigma_{imp}}) \cdot \varphi_{\varepsilon_j}, \qquad j \geq 1 \tag{18}$$

subject to:

$$\tau_{\varepsilon_{j_1-1}} < \tau_{\sigma_{imp}^{i-1}} < \tau_{\varepsilon_{j_1}}, \qquad 2 \leq i \leq |\sigma_{imp}| \tag{19a}$$

$$\tau_{\varepsilon_{j_2}} + \varphi_{\varepsilon_{j_2}}/2 = \tau_M < \hat{\tau}_{\sigma_{imp}^{i}}, \qquad 1 \leq i \leq |\sigma_{imp}| \tag{19b}$$

$$\tau_{\sigma_{imp}^{0}} = 0 \tag{19c}$$

In the search of $\tau_{\sigma_{imp}^{i}}$ based on existing $\tau_{\sigma_{imp}^{i-1}}$, if for a specific j both $\hat{\tau}_{\sigma_{imp}^{j}}$ and the first value of τ_I exceed T (the duration of the planning horizon), then the numerical search is terminated. For all $i \geq j$, values of $\tau_{\sigma_{imp}^{i}}$ are set to T, and the binary indicators $\beta_{\sigma_{imp}^{i}}$ equal 0.

Genetic algorithm for project selection and sequence optimization

The optimization of the long-term improvement plan in the upper-level model uses a customized genetic algorithm (GA) whose operator settings are based on those used in Wu et al. [29].

To tackle the selection and sequencing of improvement projects, some chromosome representations and operator settings are modified. In population initialization, after generating each chromosome by randomly arranging integers 1 to $|\Lambda|$, each location in the chromosome has a specified probability that the number is replaced with a blank. When evaluating each chromosome, blank locations are removed, and the remaining sequence of numbers represents the implementation sequence of improvement projects. In the crossover operator, the blank locations are temporarily filled with numbers so that each integer from 1 to $|\Lambda|$ appears in each chromosome exactly once. These locations move together with their corresponding numbers and return blank at the end of crossover. In the mutation operator, in addition to equiprobable swapping or insertion, a given probability is assigned to the action that selects a random location and turns the number in it into a blank or vice versa (ensuring that no numbers repeat in a chromosome). For each improvement sequence to be evaluated, the algorithm checks whether it has been previously evaluated by looking for it in a list. If yes, its corresponding objective function value is directly retrieved from the list to avoid repetitive computation. Otherwise, the objective function value is computed for this “new” sequence and recorded in the list along with the sequence.

NUMERICAL RESULTS

Optimizing long-term improvement plan with underlying Frank-Wolfe Algorithm

To demonstrate the proposed integrated optimization model, a road network based on the Sioux Falls network [30] is used in the numerical case as shown in Figure 4. Each existing link has its numeric label. All links shown in the figure are two-directional, with equal numbers and widths of lanes in their two directions. The length of each link (in miles) and its total one-directional capacity (in vehicles per hour) are labelled in the figure. This network is modeled using NetworkX, a Python package. This package also assists the Frank-Wolfe algorithm by finding the shortest path for each OD pair.

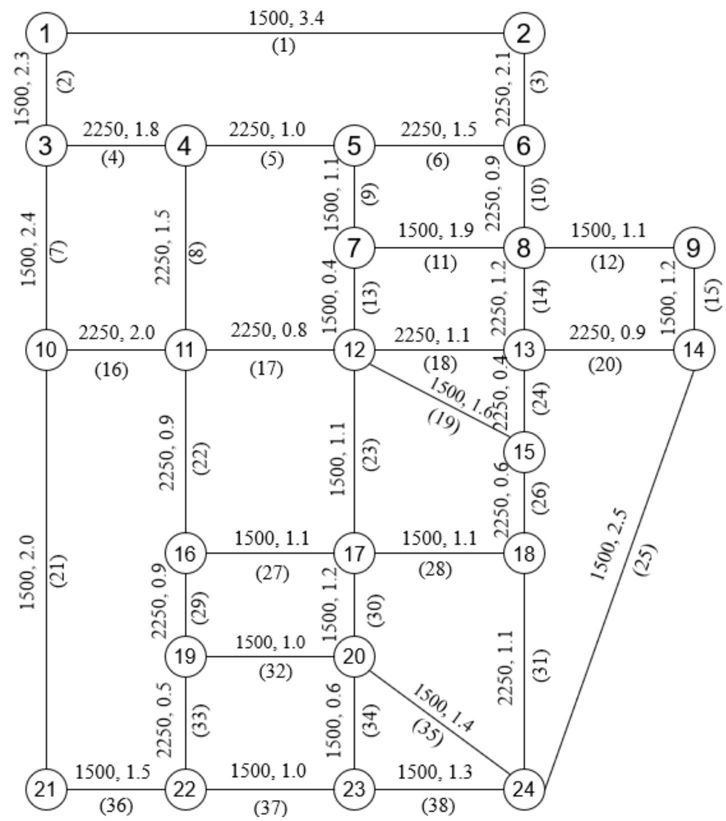


Figure 4 The example Sioux Falls road network

For traffic simulations, all lane widths are assumed to be 11 feet. In each direction, links (3), (4), (5), (6), (8), (10), (14), (16), (17), (18), (20), (22), (24), (26), (29), (31), and (33) have three lanes, and the others have two lanes. Lane capacity throughout the network is 750 vehicles per hour per lane. The normal free flow travel times through links are based on the normal free flow speed of 30 miles per hour.

Original hourly travel demands in vehs/hr by OD pair are shown in Table 2. This demand level lasts for 18 hours a day, with H = 6,570 hours per year.

Table 2 Original hourly demands by OD pair in vehicles/hour

To \ From	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1		180							270				240				150							
2							240			270						120						90		
3					210	150					210			210										
4								180				180						120			180			
5			150							210					180				90					
6	240							240									180						150	
7				240					300				300											240
8		300									330				300					240				
9						300						360						240			270			
10							330							300	270				240					
11		240										270								270		240		

12								330									270	270					270	
13			360							330						240					300			
14	270						300												300					210
15				270	330						300											240		
16	210				180				240											150				
17						210					240					180								120
18					210									240							150		210	
19			180				210										120					180		
20												150		180	150								120	
21									300				210			150		180						
22			210	150				240																120
23	150					180							240						150					
24		120		180						240										180				

In a planning horizon of T=10 years, there are 6 candidate improvement projects that increase link capacities upon their completion (the increase rates are based on the original values in Figure 4):

Table 3 Candidate improvement projects and their parameters in the road network

Proj. #	Description	Construction cost C_l (×\$10^6)	Required work time ϕ_l (years)
1	Increasing capacities of links 4, 5, 6 by 1/3	8.6	0.75
2	Increasing capacities of links 11, 12, 15 by 1/3	8.4	0.75
3	Increasing capacities of links 27, 28, 31 by 25%	6.6	0.75
4	Increasing capacities of links 8, 22, 29, 33 by 25%	5.7	0.75
5	Increasing capacities of links 23, 30, 34 by 25%	4.35	0.5
6	Increasing capacities of links 21, 36, 37, 38 by 20%	11.6	1

When projects 1, 2, 3, and 6 are under construction, capacities of affected links decrease from the base values by 25%, and travel times through them increase by 1/3. When projects 4 and 5 are under construction, capacities of affected links decrease by 20%, and travel times through them increase by 25%.

The unit value (cost) of travel time (v) is \$15/veh/hr. The planning horizon is first divided into 10 sub-periods of 1 year and further divided by the starting and completion times of projects. The annual interest rate r is 5%, and the annual growth rate of demand g is 2.5%. In addition to the annual external budget supply F = \$9×10^6, a fraction μ = 1% of total travel time cost is used as the internal source of the improvement budget. In the F-W traffic assignment algorithm the threshold of Δ_x in equation (13) is 0.001. When determining the budget-ready times of implemented projects, the threshold of Δ in equation (18) is \$1,000. GA parameters are set as follows: *pop_size* = 30, *best_chroms* = 2, *max_iter* = 150, *max_stall* = 30, *p_c* = 0.5, *p_m* = 0.8, *sel_pres* = 0.06.

The model and the numerical case are coded in Python 3.7.3. The program is run on a personal laptop with an Intel® Core™ i7-8750H CPU @ 2.20GHz. With the lower-level UE traffic assignment conducted by the F-W algorithm, the GA-optimized solution is represented by (4, 1), which means that projects 4 and 1 are selected and sequentially completed within the planning horizon. Project 4 and Project 1 are started at 0 years and 0.4433 years into the planning horizon, respectively, and are completed at 0.75 years and 1.1933 years into the planning horizon. The resulting minimized PVC is \$$3.39405\times10^9$. The computation time is 3604.6 seconds. This GA-optimized solution is the global optimum, as shown by exhaustive enumeration.

With the same set of dividing times, the change in non-discounted hourly travel time cost with the optimized improvement plan is compared with that without any network improvement in the first 4 years of the planning horizon, as shown in Figure 5. While the construction of projects temporarily increases the hourly travel time cost, their completion reduces it in the long run.

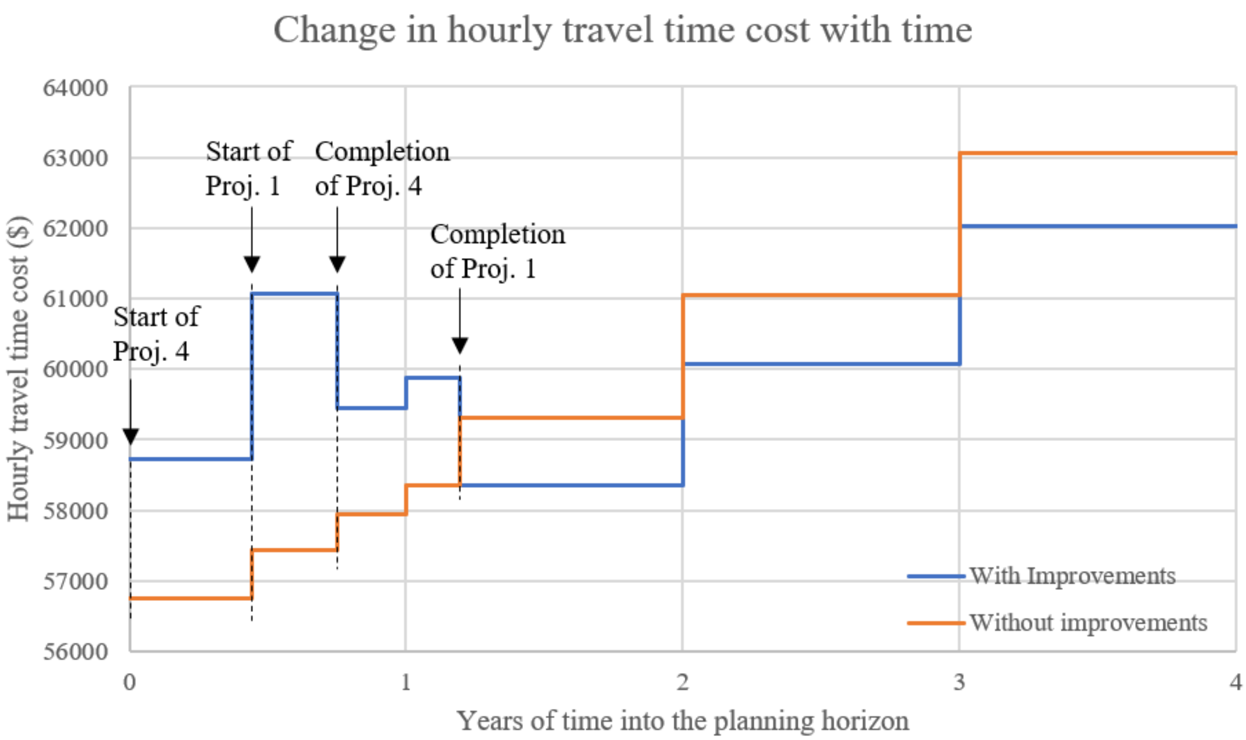


Figure 5 Effects of improvements in hourly travel time cost

Comparing two lower-level computation methods with example improvement sequences

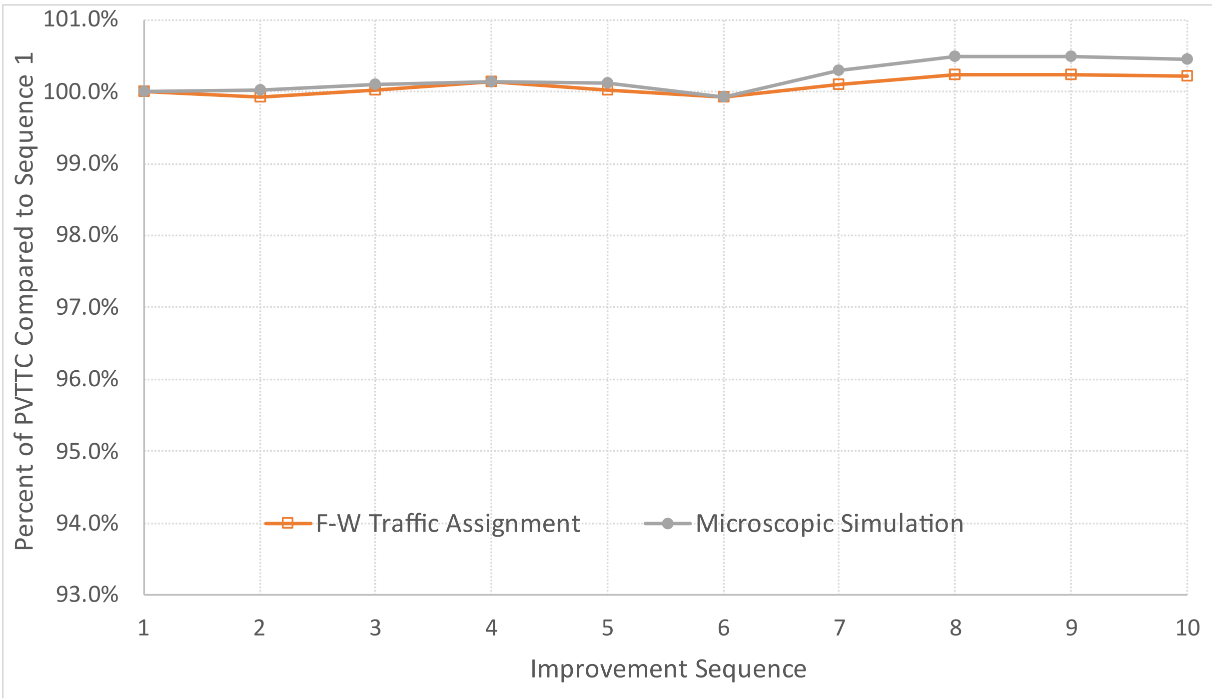
The two lower-level computation methods described above represent different approaches in terms of their underlying logic. While the traffic assignment using the F-W algorithm is computationally efficient in evaluating improvement sequences within an optimization framework that employs a global objective function and a set of constraints, it falls short in modeling crucial aspects such as vehicle interactions, stop-and-go behavior resulting from traffic controls or congestion, and the related delays and shockwaves. Consequently, it proves insufficient in fully capturing the intricate details of traffic conditions, particularly in congested scenarios. To comprehensively account for factors such as vehicle-to-vehicle and vehicle-to-control interactions, which significantly contribute to delays, it becomes necessary to incorporate these elements when computing the present values of travel time cost (PVTTC, not including the present value of construction costs). Thus, a higher-fidelity tool is required to validate the evaluation results obtained only through traffic assignment using the F-W algorithm. INTEGRATION, a microscopic traffic simulation model, should enable a more accurate and realistic representation of traffic dynamics under various conditions.

The results of the two lower-level computation methods are compared across ten example improvement sequences where different combinations of improvement projects are applied. The ten sequences labeled from No.1 to No.10 are represented by: (2), (4, 1), (6, 4), (1, 5, 6), (3, 2, 5), (4, 5, 2), (5, 6, 4, 1), (2, 3, 6, 1, 5), (3, 5, 1, 6, 2, 4), and (6, 2, 5, 1, 4, 3). When computing the PVTTC of these sequences, the starting and completion times of projects are first determined using the F-W traffic assignment at the lower level and the baseline demand level as shown in Table 2. For each of these sequences, regardless of the method applied at the lower level (F-W traffic assignment or microscopic simulation) and the varied demand levels, the same set of starting and completion times is used as the division times of sub-periods. To examine the impact of demand level on the PVTTCs evaluated with two methods in the lower-level model, the demand level varies at 25%, 40%, 50%, 60%, and 75%, in addition to the original 100% flow rate. Table 4 presents the PVTTCs of the ten example improvement sequences computed under different demand levels with two methods. Given a demand level and using one of the two methods, each PVTTC value is marked with its ranking among the ten sequences (a lower PVTTC means a higher ranking) inside the parentheses.

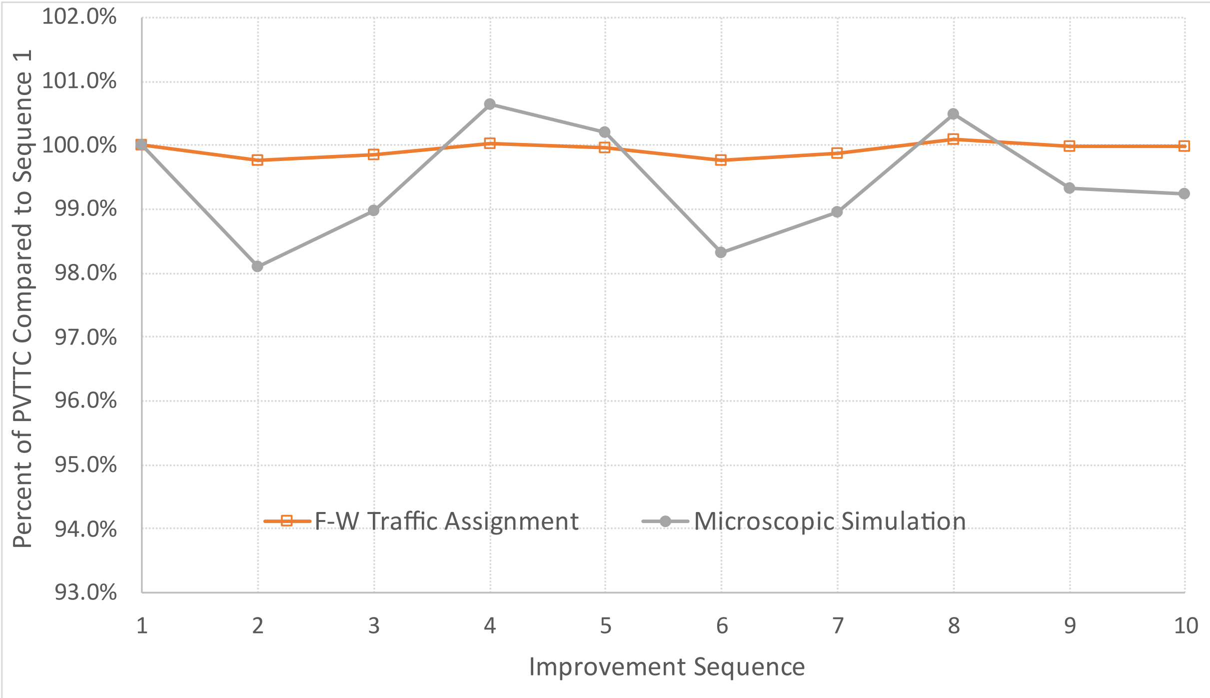
Table 4 PVTTCs and their rankings with different demand levels and lower-level methods

Using F-W traffic assignment at the lower level							
Seq. No.	Improvement sequence	PVTTC (×$$10^8$) at different demand levels (Ranking inside parentheses)					
		25% demand	40% demand	50% demand	60% demand	75% demand	100% demand
1	2	6.6449(3)	11.1972(8)	14.4782(10)	17.9626(10)	23.5893(10)	34.1053(10)
2	4→1	6.6406(2)	11.1715(2)	14.4285(1)	17.8805(1)	23.4428(4)	33.8032(4)
3	6→4	6.6460(4)	11.1810(3)	14.4427(4)	17.9039(6)	23.4762(6)	33.8544(6)
4	1→5→6	6.6543(7)	11.1994(9)	14.4664(7)	17.9303(7)	23.5105(8)	33.8997(8)
5	3→2→5	6.6463(5)	11.1935(5)	14.4671(8)	17.9410(9)	23.5438(9)	33.9942(9)
6	4→5→2	6.6396(1)	11.1708(1)	14.4315(2)	17.8913(3)	23.4628(5)	33.8385(5)
7	5→6→4→1	6.6519(6)	11.1839(4)	14.4390(3)	17.8862(2)	23.4369(1)	33.7564(3)
8	2→3→6→1→5	6.6612(10)	11.2077(10)	14.4726(9)	17.9332(8)	23.5046(7)	33.8648(7)
9	3→5→1→6→2→4	6.6605(9)	11.1967(7)	14.4518(6)	17.8975(5)	23.4380(2)	33.7275(1)
10	6→2→5→1→4→3	6.6596(8)	11.1951(6)	14.4504(5)	17.8968(4)	23.4390(3)	33.7349(2)
Using microscopic simulation at the lower level							
Seq. No.	Improvement sequence	PVTTC (×$$10^8$) under different demand levels (Ranking inside parentheses)					
		25% demand	40% demand	50% demand	60% demand	75% demand	100% demand
1	2	8.8430(2)	16.8429(7)	32.8747(9)	52.7318(8)	78.7471(10)	131.3138(10)
2	4→1	8.8461(3)	16.5242(1)	30.9310(2)	50.4549(4)	75.9464(6)	125.9006(5)
3	6→4	8.8515(4)	16.6694(4)	31.0122(3)	49.8583(2)	75.9089(5)	127.3430(6)
4	1→5→6	8.8564(6)	16.9514(10)	32.6763(8)	52.1586(7)	77.7070(8)	127.4763(7)
5	3→2→5	8.8532(5)	16.8783(8)	32.9712(10)	52.8387(10)	77.9042(9)	130.1717(9)
6	4→5→2	8.8363(1)	16.5594(2)	30.6847(1)	49.5406(1)	75.1790(4)	125.0906(1)
7	5→6→4→1	8.8689(7)	16.6680(3)	31.4211(7)	50.2621(3)	74.5916(1)	125.1169(2)
8	2→3→6→1→5	8.8857(9)	16.9269(9)	33.3313(4)	52.8018(9)	76.9717(7)	128.8017(8)
9	3→5→1→6→2→4	8.8863(10)	16.7298(6)	31.3504(5)	50.8736(6)	74.9340(2)	125.3844(3)
10	6→2→5→1→4→3	8.8833(8)	16.7158(5)	31.4081(6)	50.6188(5)	75.1222(3)	125.6325(4)

Figure 6 illustrates the PVTTCs of sequences 2 through 10, plotted against the PVTTC of sequence 1 as the baseline (100%). Notably, the two methods consistently rank the candidate sequences similarly. However, the network exhibits varied improvement results for each sequence. The INTEGRATION model, in particular, demonstrates more variations due to its microscopic simulation capabilities, which allow it to capture the effects of traffic congestion (including supersaturated conditions), traffic signal delays, and other real-world delays.



(a)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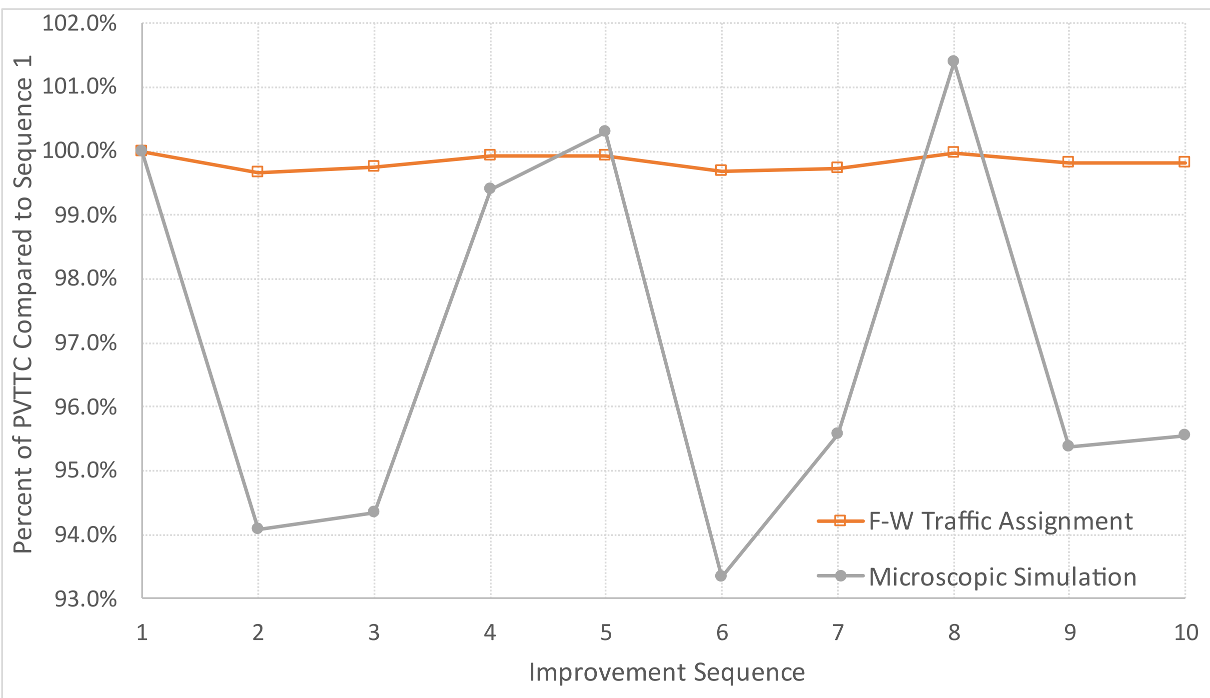
(b)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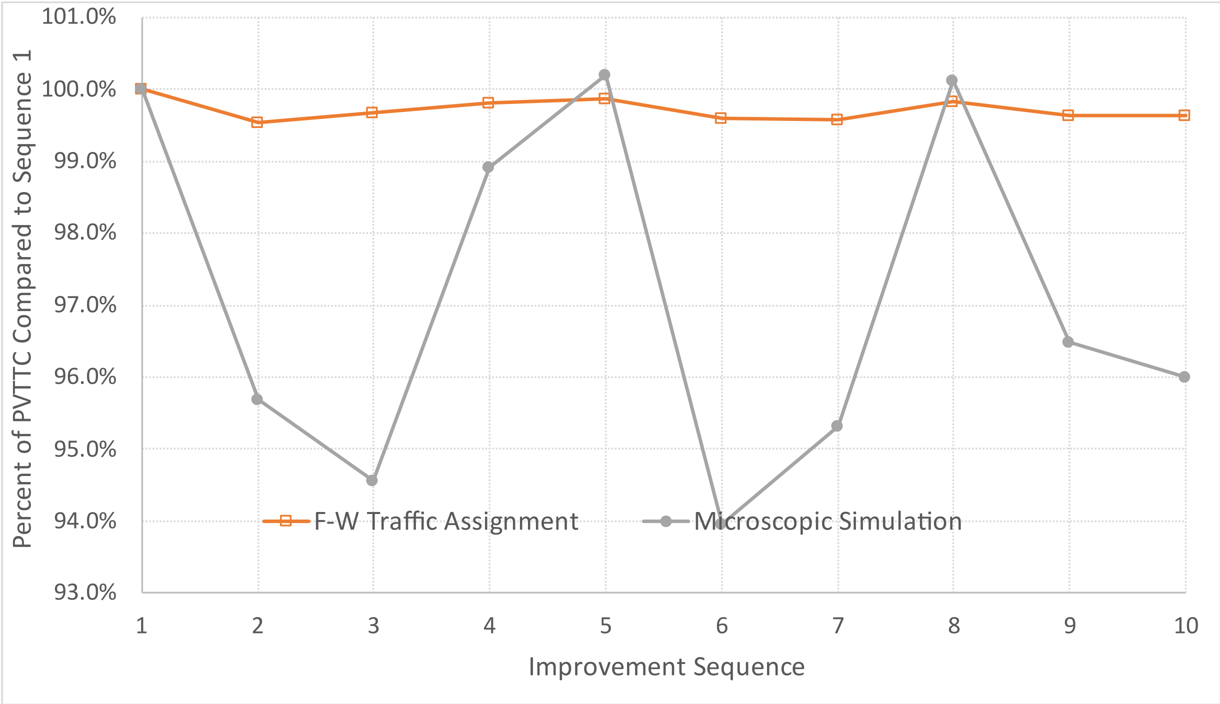
(c)



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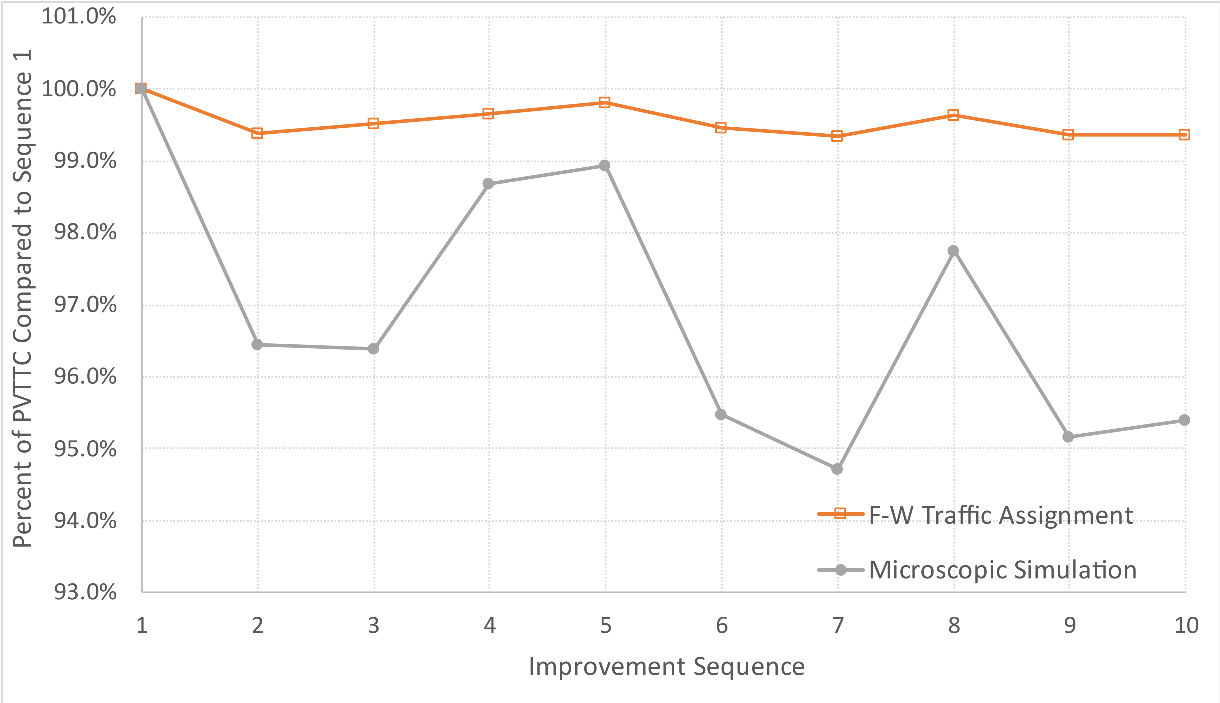
Improvement Sequence

(d)



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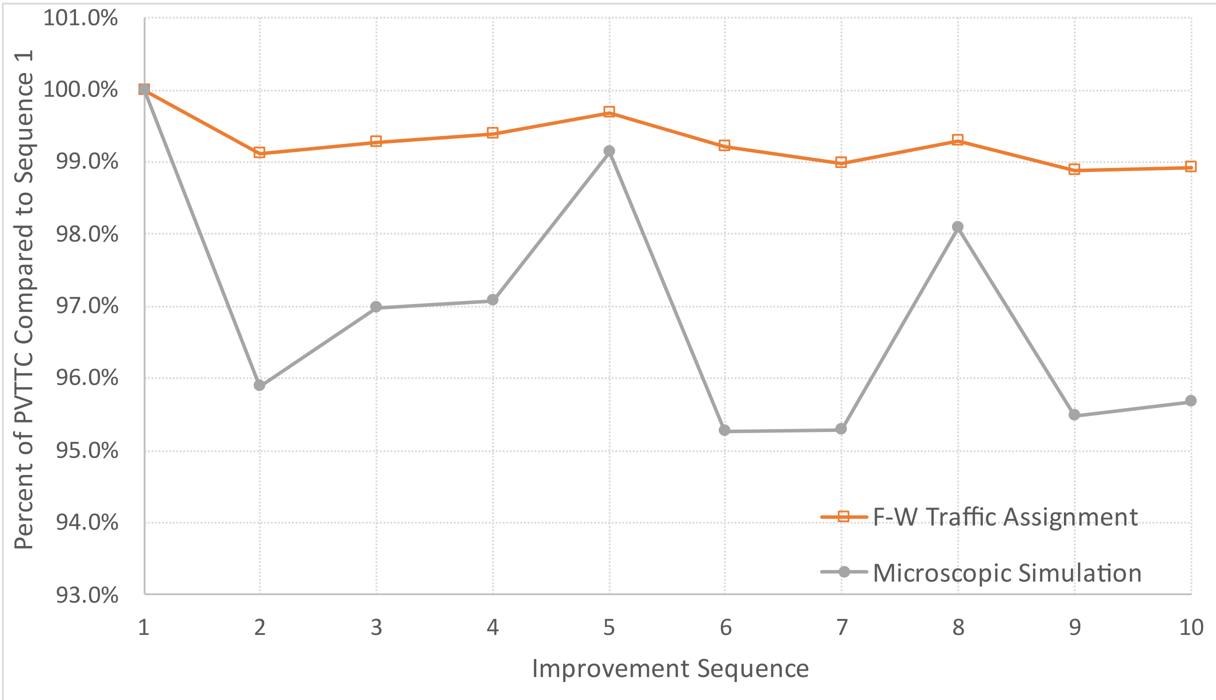
(e)



(f)

Figure 6 PVTTC of improvement sequences compared to sequence 1 (at demand level of (a)25%, (b)40%, (c)50%, (d)60%, (e)75%, (f)100%)

One key distinction between the two methods lies in the microscopic feature of INTEGRATION. By capturing the interactions of individual vehicles, INTEGRATION models delays and congestion in a way that reflects the instability of a network under congested conditions. This feature provides a more detailed understanding of how demand levels affect the results of the two methods. To investigate this further, the PVTTC rankings of the 10 sequences based on the results generated by two different lower-level methods are compared using the rank correlation coefficient ρ, for all the demand levels $d \in D$:

$$\rho = \sum_{s=1}^{10} (R_{s,ms}^{d} - R_{s,ta}^{d})^2, \forall d \in D \tag{20}$$

where $R_{s,ms}^{d}$ is the ranking of the s^{th} sequence using microscopic simulation and $R_{s,ta}^{d}$ is the ranking of the s^{th} sequence using F-W traffic assignment. Figure 7 presents the variation of ρ at different demand levels.

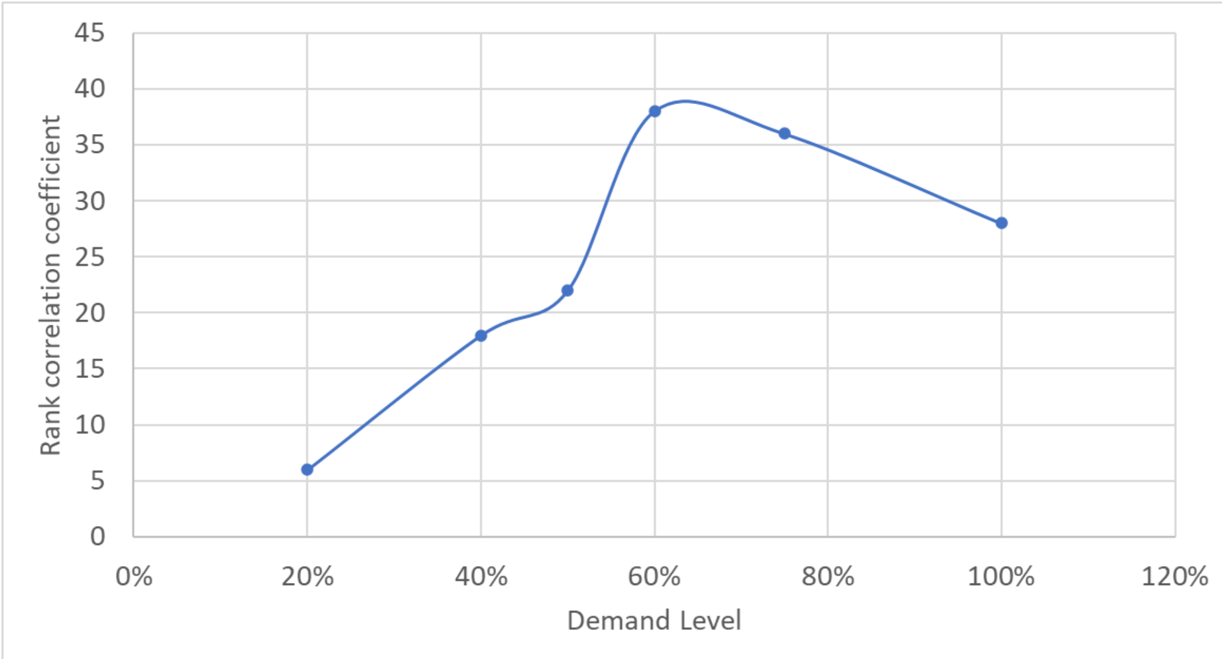


Figure 7 Change in rank correlation coefficient with the varying demand level

As observed, the disparity in rankings between the two methods initially remains minimal when the network operates in free-flow conditions. However, this discrepancy progressively grows with increasing demand levels and reaches its peak when the network becomes congested. The microscopic simulation, with its capability to capture delays arising from congestion and traffic control devices, contributes to the widening gap between the two rankings. As congestion intensifies, vehicles may start to wait outside the network, and their waiting time is not accounted for, yielding a relative stable divergence between the two methods when demand level is above 70%. This outcome aligns with the findings of Aljamal et al. [31], which suggest that INTEGRATION effectively captures fluctuating congestion and accurately reflects the escalating travel time resulting from higher traffic demand and reduced roadway capacities.

CONCLUSIONS

The presented work focuses on optimizing selection, sequencing, and scheduling of interrelated projects in road networks while highlighting the comparison of two methods for travel time evaluation.

For road networks, a bi-level model is designed for jointly assigning traffic to user equilibrium (UE) at the lower level and optimizing the selection and sequencing of network improvement projects at the upper level. Each improvement sequence is mapped to a unique schedule based on binding budget and work duration constraints. The planning horizon is divided into short sub-periods to approximate the effects of demand growth and cost discounting. The lower-level model computes the average hourly travel time cost in each sub-period under the time-varying network configuration, and the upper-level model minimizes the expected present value of cost (PVC, cumulative travel time cost plus project construction cost) over the planning horizon. A set of methods is proposed for determining budget-ready times of projects with internal budget supply enabled. The model is demonstrated in a numerical case, where the selection and sequencing of 6 candidate improvement projects is optimized by a customized GA.

Using ten example improvement sequences, two lower-level methods–F-W traffic assignment and microscopic simulation–are compared concerning their consistencies and performances in evaluating travel time costs under multiple demand levels. When the network is in uncongested conditions with nearly free-flow travel times, the two methods yield similar results in terms of the rankings of estimated present value of travel time cost (PVTTC) for different improvement sequences. However, as the congestion level heightens in the road network, the precision of microscopic simulation becomes evident in capturing the fluctuations at a macroscopic level by aggregating the dynamics of individual vehicles. The varying PVTTC rankings of the example improvement sequences using two different lower-level methods indicate that, particularly in congested situations, microscopic simulation emerges as a more appropriate and reliable tool for computing total travel time in road networks.

This work can be extended in the following aspects:

1) The effects of completed improvement projects on the demand level as well as those of demand elasticities on equilibrium traffic flows may be considered.
2) The model may be tested in a larger network with more candidate projects, where other heuristic methods may be applied for the upper-level optimization and compared.
3) More general forms of budget accumulation, demand growth, and congestion function may be included.
4) Uncertainties of multiple correlated parameters may be considered, and the network improvement may be optimized in a stochastic context.

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AUTHOR CONTRIBUTIONS

All authors contributed to the study conception and design, analysis and interpretation of results, and draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

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